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Carbon uptake by European agricultural land is variable, and in many regions could be increased: Evidence from remote sensing, yield statistics and models of potential productivity

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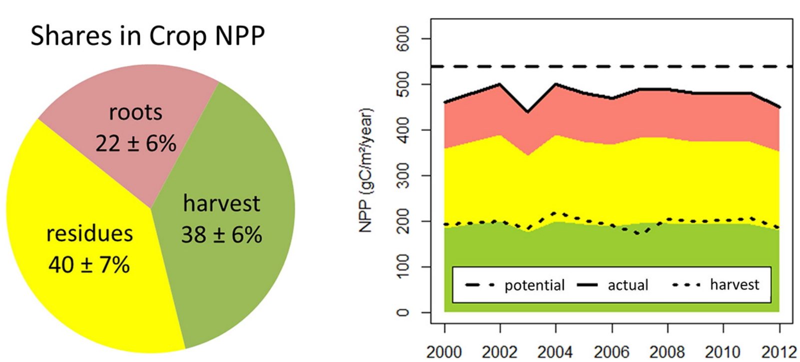
HIGHLIGHTS

- We provide robust consistent carbon uptake information for agricultural lands.
- European agriculture exhibits a yield gap of 10%, in particular in the south and east
- Agricultural plants allocate about 40% of carbon into aboveground harvestable parts.
- In Europe crops have a higher carbon uptake than forests (409 vs. 292 Mt C per year).

GRAPHICAL ABSTRACT



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ABSTRACT

Agricultural plants, covering large parts of the global land surface and important for the livelihoods of people worldwide, fix carbon dioxide seasonally via photosynthesis. The carbon allocation of crops, however, remains relatively understudied compared to, for example, forests. For comprehensive consistent resource assessments or climate change impact studies large-scale reliable vegetation information is needed. Here, we demonstrate how robust data on carbon uptake in croplands can be obtained by combining multiple sources to enhance the reliability of estimates. Using yield statistics, a remote-sensing based productivity algorithm and climate-sensitive potential productivity, we mapped the potential to increase crop productivity and compared consistent carbon uptake information of agricultural land with forests. The productivity gap in Europe is higher in Eastern and Southern than in Central-Western countries. At continental scale, European agriculture shows a greater carbon uptake in harvestable compartments than forests (agriculture 1.96 vs. forests 1.76 t C ha^{-1} $year^{-1}$). Mapping productivity gaps allows efforts to enhance crop production to be prioritized by, for example, improved crop cultivars, nutrient management or pest control. The concepts and methods for quantifying carbon uptake used in this study are applicable worldwide and allow forests and agriculture to be included in future carbon uptake assessments.

1. Introduction

Cropland occupies 11.7% of the world's land surface, with 80% of this area rain-fed and 20% irrigated (FAO, 2011). The importance of

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agriculture to the global carbon (C) cycle is well recognized. Direct emissions from the agriculture, forestry and other land use (AFOLU) sector account for 24% of anthropogenic greenhouse gas emissions in 2010 (Smith et al., 2014; Tubiello et al., 2013). Other non-greenhouse-gas-mediated effects such as albedo changes due to AFOLU also affect climate (Kirschbaum et al., 2013). Agriculture, therefore, substantially affects our climate and the global C balance (Bondeau et al., 2007; Ciais et al., 2010; Monfreda et al., 2008; Smith, 2004; Smith et al., 2008).

Although a large number of models for estimating crop production exist, such models often only capture agriculture, or only certain crop types (Elliott et al., 2015; Palosuo et al., 2011), often cannot provide temporal-continuous information or operate at coarse spatial resolution (Ciais et al., 2010). Such restrictions limit our ability to quantify C uptake by vegetation accounting for small-scale variation of soil fertility, fragmentation of land use, management patterns, disturbances etc.

C absorbed via photosynthesis is stored in carbohydrates and the total assimilated C is the Gross Primary Production (GPP). About half of GPP is soon released to the atmosphere via autotrophic respiration (Zhao et al., 2005). The remaining part, the Net Primary Production (NPP), is allocated into compartments with a longer residence time such as leaves, roots or other structures (Scurlock and Olson, 2002). About two thirds of NPP is allocated into fine roots and litterfall, both exhibiting a high turnover rate and low residence time (Malhi et al., 2011; Zhang et al., 2008). The rest is allocated into plant biomass (stem, coarse roots, leaves, fruits, grains or tubers) and, depending on the land management, is consumed by humans and animals for food or fiber, is used for bioenergy, or left in the field where it decomposes, with a small fraction remaining in longer-lived pools in soil organic matter (Smith et al., 2010).

Net Primary Production can be directly measured by quantifying its compartments (allocation into biomass, above- and belowground turnover), yet there are few measurements available (Scurlock and Olson, 2002). Models can utilize this scarce but highly valuable information. Using a single consistent model, that can deliver information of C uptake by forests, croplands and other land cover types such as savannahs and shrublands, would avoid biases arising from input data and cross-border effects by sampling or modelling concept. Remote sensing data may be useful for crop monitoring and forecasting of yield (de Wit and van Diepen, 2008). A model using satellite remote sensing information and capturing all land cover types worldwide is MOD17, which provides productivity information since the year 2000 at 1-km resolution (Zhao et al., 2005; Zhao and Running, 2010). MOD17 combines a biogeochemical model framework with satellite-based, remotely-sensed vegetation information, derived from the MODIS sensor (MODerate-resolution Imaging Spectroradiometer) on board the TERRA and AQUA satellites, operated by the National Aeronautics and Space Administration (NASA) of the United States of America. Since MOD17 NPP was validated for croplands with data from only site in North America (Turner et al., 2006, 2005), evaluation with large-scale European crop statistics may enhance our knowledge on the reliability of MOD17 outputs.

Running MOD17 with high-resolution European climate data (E-OBS) resulted in an improved regional NPP dataset (MODIS EURO) (Neumann et al., 2016b). MODIS EURO has already been shown to capture the productivity of European forests, showing average European NPP to be about 17% lower than NPP derived with global climate input (Zhao and Running, 2010). We hypothesize here that MODIS EURO will also provide robust and realistic productivity estimates for European croplands. Beyond capturing average multi-year plant productivity, MODIS EURO may even be able to identify productivity gaps spatially and temporally due to suboptimal management, since MODIS EURO has already proved to be useful for predicting annual tree mortality (Neumann et al., 2017).

An enhanced understanding of croplands would benefit ongoing discussions on trading carbon for food (West et al., 2010), and for better managing available land under yield stagnation in many parts of the world (Brisson et al., 2010; Lobell et al., 2011). The C in harvested crops is mainly consumed and respired quickly, so does not represent a significant C sink, except potentially in agricultural soils (Smith et al., 2010). Nevertheless, there should be substantial in situ C storage in crop plants during the vegetation period, so we need robust information on C uptake of agriculture (in addition to forests) to better manage the global land surface to provide resources (food, timber, fiber, etc.) and C sequestration (in situ stocks, substitution of fossil products, etc.).

This study has the following objectives:

- evaluate productivity of agricultural lands temporally from 2000 to 2012 by comparing terrestrial reference NPP using EUROSTAT data, MOD17 NPP and potential NPP calculated using the Miami model and global crop models,
- assess the potential to increase carbon uptake using productivity gap analysis, comparing potential and actual NPP, and
- explore the potential of the methods used here to assess carbon uptake across land use types

2. Materials and methods

Consistent spatially- and temporally-explicit information on C allocation would enable C uptake by vegetation to be quantified independent of country borders, inventory design or missing data. MODIS data allows estimation of plant productivity using the MOD17 algorithm (Zhao et al., 2005; Zhao and Running, 2010), which integrates biogeochemical principles with daily climate input and provides annual NPP and GPP (Net and Gross Primary Production). MOD17 was developed and globally parametrized in the early 2000s using NPP observations (Zhao et al., 2005). We evaluate crop NPP provided by MOD17 temporally from 2000 until 2012 using terrestrial reference NPP and potential NPP calculated using the Miami model (Lieth, 1975) and global crop models (Elliott et al., 2015; Mueller et al., 2012).

2.1. MOD17 NPP

MOD17 provides information on annual C uptake of all terrestrial vegetation types. Such information can be validated with reference data such as forest inventory data for forests (Neumann et al., 2016b) or yield statistics for agricultural land (Monfreda et al., 2008). To our knowledge MOD17 output has not before been validated with European yield statistics. MOD17 employs the radiation use efficiency logic introduced by Monteith (1972) and accounts for C lost by respiration by incorporating basic allometric relations in a respiration module (Zhao and Running, 2010). The key inputs are gridded meteorological data (minimum and maximum temperature, precipitation), remotely sensed vegetation properties (Leaf Area Index, Fraction Absorbed Radiation) and physiological biome properties (e.g. Specific Leaf Area, Maximum light Use Efficiency) pertaining to the local biome type. The MOD17 algorithm is explained in more detail elsewhere (Neumann et al., 2016b; Zhao et al., 2005; Zhao and Running, 2010).

MOD17 provides NPP estimates for a total of 11 land cover types such as evergreen needleleaf forests, mixed forests, grass- and croplands based on the MOD12Q1 land cover map, which uses the University of Maryland (UMD) classification system (Friedl et al., 2010). The MOD12Q1 algorithm for grasslands is parametrized to capture regions with continuous cover with herbaceous plants (Friedl et al., 2010; Hansen et al., 2000). “MODIS grasslands” are thus mostly found in high elevation and in Turkey (Fig. S1) and do not capture pastures or meadows used for grazing, an important type of European agriculture, which appear in the “croplands” category. We evaluated MODIS land cover with two other data sources (EUROSTAT, CORINE land cover) to quantify the share of pasture and test its accuracy. Our study region is constrained by availability of MODIS EURO and EUROSTAT data and covers EU-27, including Norway, Switzerland and the Balkans (Fig. 1).

We used MODIS EURO, obtained by re-running the MOD17 algorithm with downscaled climate data from the E-OBS database

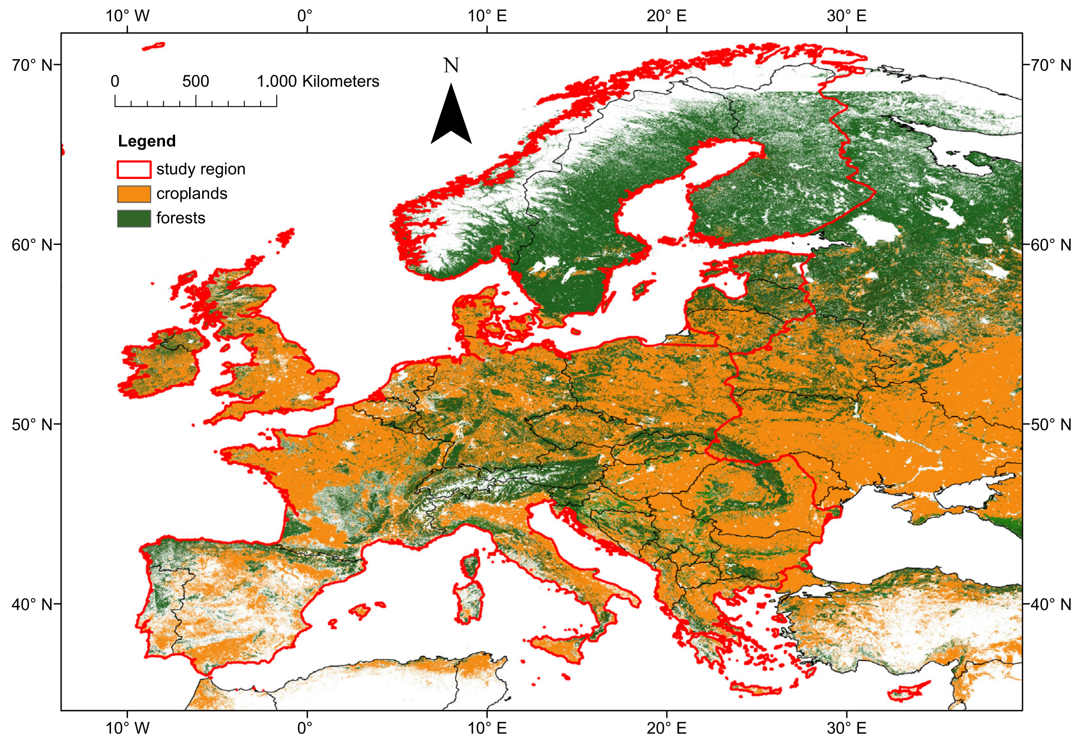

Fig. 1. Distribution of croplands (including pastures and permanent crops such as grapes, olives, fruits, etc.) and forests in Europe based on MODIS satellite data and the UMD classification system (Friedl et al., 2010). White regions are mostly shrublands, savannahs, water, and urban areas.

(Neumann et al., 2016b), which was validated by meteorological station data (Moreno and Hasenauer, 2016) and is, to our knowledge, one of the best available gridded daily climate datasets. We consequently did not consider varying the climate input for MOD17 to express uncertainty.

2.2. NPP using yield statistics

EUROSTAT, the European Statistics Organization, provides statistical data on, for example, economic indicators, population, industry and agricultural production in the European Union (EUROSTAT, 2015). We obtained current EUROSTAT crop statistics from 2000 onwards at country level (agr_apro_acs_a) on the 14, March 2017. We used data from 2000 to 2012, since MODIS EURO is available until 2012. We calculated annual yield (tonnes per hectare per year) for the most important crop types (Table S1) by dividing production mass (e.g. 1000 t) by production area (e.g. 1000 ha). EUROSTAT does not provide measures of uncertainty either for production or area since it is compiled from country level statistical returns, thus it was not possible to analyze this potential source of uncertainty. Harvested production reported to EUROSTAT represents “wet yield” and thus contains varying water content depending on crop type, country and year. For most crop types, EUROSTAT provides the water content in the reported production mass.

The primary output of EUROSTAT crop statistics is wet yield in t ha^{-1} year^{-1}. For comparison with MOD17 we need Net Primary Production (NPP) in g C m^{-2} year^{-1} and we estimated NPP using wet yield data as follows:

$$\mathrm{NPP} = \text{wet yield} \times (1-\mathrm{WC})/\mathrm{HI} \times (1+\mathrm{RS}) \times \mathrm{CC} \tag{1}$$

where WC is water content, HI is harvest index, RS is root-shoot ratio, and CC is carbon content (%) (Monfreda et al., 2008; Niedertscheider et al., 2016).

There are several available references providing parameters to convert yield into NPP, and the suggested parameters differ between studies. Since the parameters have a large effect on the resulting productivity (i.e. HI +5% results in NPP −5% keeping other parameters the same), we used several sets of parameters to derive more robust results based on an ensemble of NPP estimates based on yield statistics. We used four methodologies cited in four previous studies (Gobin et al., 2011; Haberl et al., 2007; Monfreda et al., 2008; Niedertscheider et al., 2016). Two of these provide separate cereal HI values for East and West Europe (Haberl et al., 2007; Niedertscheider et al., 2016). We created two parameter sets for each case, which differ only in the HI values to avoid prior assumptions. This resulted in six parameter sets. For each of the six parameter sets, we calculated NPP using (1) the water content reported in the respective reference and (2) with the water content provided by EUROSTAT, which provided us with 12 NPP estimates in total. EUROSTAT provides water content only for certain crop types (Table 1) and for the remainder, we used literature values.

2.3. Potential NPP

We next computed NPP using the Miami model (Lieth, 1975). The Miami model was fitted using NPP observations of biomes close to their potential (potential natural vegetation), and represents potential NPP of a natural reference system limited only by climate conditions. We chose the Miami model since it requires little input and is thus easily applicable worldwide. Potential NPP is the minimum value of Eqs. (2) and (3), thus in some regions, plant production is limited by precipitation and in others it is limited by temperature.

$$\mathrm{NPP} = 3000 \times \left(1 - \exp^{(-0.000664\ \mathrm{P})}\right) \tag{2}$$

$$\mathrm{NPP} = 3000/\left(1 + \exp^{(1.315+\mathrm{T}\times(-0.119))}\right) \tag{3}$$

NPP calculated using Eqs. (2) and (3) represents grammes dry biomass and was converted into C using 50% CC. P is the annual average precipitation sum in mm, T the average annual temperature in °C.

Table 1
Coefficients to estimate NPP from EUROSTAT yield data by crop type (mean and standard deviation). First six rows are annual crops, followed by four permanent crops. Water content (WC) in percent is available from EUROSTAT and for each reference. HI is harvest index, the ratio of dry yield and aboveground biomass (belowground for root crops). RSR is the root-shoot ratio and CC the carbon content. HI values in brackets represent values for Western Europe; the other value is for Eastern Europe. $ indicates parameters from Monfreda et al. (2008) due to missing data in Gobin et al. (2011).

Crop type	EUROSTAT	Gobin et al., 2011, Monfreda et al., 2008				Niedertscheider et al., 2016				Haberl et al., 2007				Monfreda et al., 2008			
	WC (%)	WC	HI	RSR	CC	WC	HI	RSR	CC	WC	HI	RSR	CC	WC	HI	RSR	CC
Cereals	14.0 ± 1.7	11.0 $	0.62	0.41	0.50	14.0	0.39 (0.48)	0.32	0.50	14.0	0.39 (0.49)	0.15	0.50	11.0	0.42	0.32	0.45
Plants harvested green	39.8 ± 29.8	76.0 $	1.00	0.80	0.50	76.0	1.00	0.43	0.50	76.0	1.00	0.15	0.50	76.0	1.00	0.43	0.45
Oil crops	9.7 ± 1.9	9.6 $	0.29	0.18	0.50	9.6	0.37	0.17	0.50	9.6	0.34	0.15	0.50	9.6	0.34	0.17	0.45
Root crops	–	80.0 $	0.99	0.07	0.50	77.5	0.58	0.25	0.50	77.5	0.57	0.15	0.50	80.0	0.45	0.25	0.45
Veget., strawb.	–	87.0 $	0.45 $	0.18 $	0.45 $	87.0	0.45	0.18	0.50	87.0	0.40	0.15	0.50	87.0	0.45	0.18	0.45
Pulses	14.1 ± 2.1	10.5 $	0.47 $	0.23 $	0.45 $	10.5	0.50	0.26	0.50	10.5	0.50	0.15	0.50	10.5	0.50	0.26	0.45
Olives	–	20.0 $	0.28 $	1.00 $	0.45 $	20.0	0.28	1.00	0.50	20.0	0.40	0.15	0.50	20.0	0.28	1.00	0.45
Grapes	–	81.0 $	0.30 $	0.33 $	0.45 $	81.0	0.30	0.33	0.50	81.0	0.40	0.15	0.50	81.0	0.30	0.33	0.45
Fruits, nuts, berries	–	81.0 $	0.30 $	0.33 $	0.45 $	81.0	0.30	0.33	0.50	81.0	0.40	0.15	0.50	81.0	0.30	0.33	0.45
Citrus fruits	–	87.0 $	0.30 $	1.00 $	0.45 $	86.0	0.30	1.00	0.50	86.0	0.40	0.15	0.50	87.0	0.30	1.00	0.45

We applied the functions using long-term periodic average precipitation and temperature information from the WorldClim database at 1-km resolution, Version 1.4 representing 1960–1990 (Hijmans et al., 2005). We also computed potential NPP using WorldClim data Version 2 representing 1970–2000 and employing a different and more accurate interpolation routine (Fick and Hijmans, 2017) and using current average climate from 2000 to 2012 (Moreno and Hasenauer, 2016), used for computing MODIS EURO. We computed country mean NPP for croplands (and for forests) based on the same land cover map used for MOD17 (Friedl et al., 2010). Country-wise summaries of the used NPP data are provided in Tables S2 and S3.

We evaluated the output of the Miami model with more sophisticated gridded crop models to test whether the Miami model provides realistic productivity estimates for croplands. We collected available gridded potential yield from climate-binned yield statistics (EarthStat) available on http://www.earthstat.org/data-download/ (Mueller et al., 2012) and fully irrigated yield from three global crop models (GEPIC, PEPIC, LPJmL) available for historic conditions (1861 to 2005) on https://esg.pik-potsdam.de/search/isimip/. The four crop models provide yield in t ha^{-1} year^{-1} and to compare with the Miami model we had to convert the model output into NPP using average European conversion factors (Eq. (1)). Unfortunately, from the most important crop types in Europe (Tables 1 and S3) only results for wheat and maize were available. We show all five potential NPP estimates (GEPIC, PEPIC, LPJmL, EarthStat, Miami) on country scale in Fig. S3 and compare output of the first four with Miami NPP and with EUROSTAT NPP in Figs. S4 and S5 respectively.

2.4. Productivity gap analysis

We have three conceptually different NPP sources with respective strengths and weaknesses.

(1) EUROSTAT NPP is based on harvested, “realized” yield and conversion parameters and is thus affected by (potentially) incomplete recordings, lost harvest and inaccurate conversion parameters. EUROSTAT use harmonized guidelines to ensure quality control and comparability, yet rely on national partners (mostly Statistic Institutes) for compliance and implementation.
(2) MOD17 NPP is computed by a biogeochemical model algorithm parametrized with global crop data using remotely sensed vegetation information and gridded climate as input. The satellite-mounted sensor MODIS captures all vegetation irrespective of whether it is harvested or left on the field, but MOD17 may not capture highly productive crops such as C4 plants, or properly incorporate soil limitations and/or nutrient effects.
(3) The Miami model provides potential NPP based solely on temperature and precipitation, parametrized with NPP observations on climax vegetation close to their potential. In consequence, the Miami model provides broad values of potential productivity constrained by climate using limited input and thus can be applied on high spatial resolutions.

The productivity gap describes the gap between actual and potential productivity of crop systems, which can be expressed in terms of the harvested agricultural product as a yield gap (Van Ittersum et al., 2013). EUROSTAT and MOD17 are estimates of actual productivity, and Miami NPP estimates potential productivity. We quantified the productivity gap for Europe by calculating differences between EUROSTAT, MOD17 and Miami NPP. For EUROSTAT we compared country average NPP. For Miami and MOD17 we did a pixel-based comparison.

2.5. NPP fractions of croplands and forests

NPP comprises all C allocated into plant compartments (e.g. above- or belowground, stem or leaves). The allocation patterns may vary depending on species, evolutionary traits, plant age, genetics or management (e.g. Chen et al., 2002; Montero et al., 2005; Malhi et al., 2011). Better understanding the fate of allocated C in croplands and in forests would help quantify C removal by harvesting and formation of C pools, in combination with decomposition rates (Zhang et al., 2008). We defined three proportions of NPP: roots (coarse and fine roots), aboveground residues (litterfall, crop residues) and harvested material (yield, aboveground wood increment). Proportions of forests were assumed 36 ± 11% roots (mean ± standard deviation), 34 ± 6% litterfall and 30 ± 10% wood increment based on data from Malhi et al. (2011) considering 23% of C allocation into wood goes to coarse roots (Neumann et al., 2016a). Assuming that litterfall 34% of NPP in forests was in line with European litterfall observations (Neumann et al., 2018). For crops we took mean proportions of conversion factors (roots 22%, residues 40%, harvest 38%) compiled by this study (Table 1).

We also compiled observed aboveground harvest/yield to evaluate the computed harvest results based on MOD17 NPP, which is a model output. EUROSTAT provides C in harvested yield and forest inventory data provides C increment in aboveground tree compartments. Average C increment in trees is 235 g C m^{-2} year^{-1} and assuming 23% C in coarse roots, results in an aboveground C increment of 181 g C m^{-2} year^{-1} (Neumann et al., 2016b).

Statistical analysis and visualization were performed using ArcMap 10.0 and the “Map Algebra” tool as well as R language and environment for statistical computing (R Development Core Team, 2016). A summary of used agricultural data is provided in the Supplementary Information. MODIS EURO NPP data can be obtained at ftp://palantir.boku.ac.at/Public/MODIS_EURO/.

3. Results

3.1. Area and productivity of European agricultural land

Agricultural land represents a large share of European land area, between 40% and 45% depending on the data source (Table 2). Although the three estimates of agricultural area in general largely agree, there are considerable differences at country scale. Pasture represents about 8% of the total land area in Europe and 17% of the agricultural area. For certain countries, the share of pasture in agricultural land can be considerably higher (e.g. Ireland 76%, United Kingdom 47%, Netherlands 43%).

Potential European average NPP using the Miami model varied slightly depending on the climate input (WorldClim v1.4: 571 ± 147 g C m^{-2} $year^{-1}$, WorldClim v2.0: 571 ± 152 g C m^{-2} $year^{-1}$, downscaled E-OBS: 527 ± 124 g C m^{-2} $year^{-1}$). Average European crop NPP for 2000 until 2012 using the MOD17 algorithm was 500 ± 82 g C m^{-2} $year^{-1}$. The annual variation was ± 15 g C m^{-2} $year^{-1}$ (see Table S2 for country results). For each country and each year we calculated 12 NPP estimates based on EUROSTAT data (European average for 2000–2012: 476 ± 51 g C m^{-2} $year^{-1}$), and provide an example (Table S1) to demonstrate the steps needed to convert reported yield into NPP. Considering this variation, and comparing the envelope of the 12 EUROSTAT NPP estimates and MOD17 NPP from 2000 until 2012 with potential NPP from the Miami model in Fig. 2, indicates that MOD17 agrees quite well with EUROSTAT data, which shows considerable variation, depending on the conversion parameters used. Potential NPP from the Miami model exceeds MOD17 results by about 50 g C m^{-2} $year^{-1}$. A version of Fig. 2 showing the single EUROSTAT estimates is provided as Fig. S2 in the Supplementary Information.

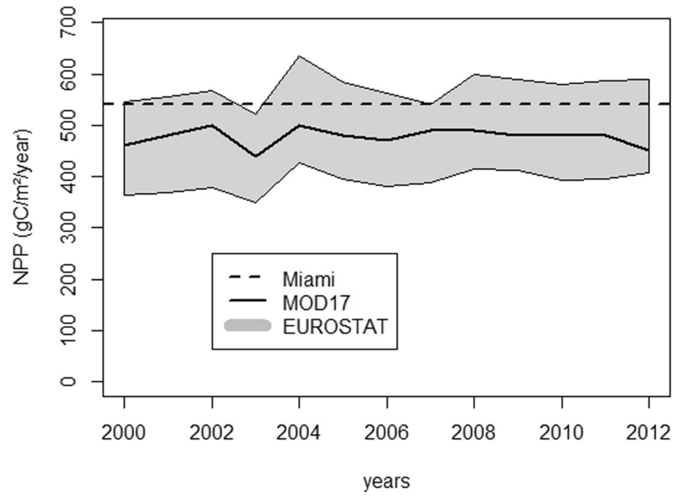

Fig. 2. Comparison of MOD17 NPP for croplands with an ensemble (n = 12) of NPP estimates using EUROSTAT yield data and conversion factors from the literature (min–max envelope). The dashed line represents potential NPP using the Miami model and Worldclim v1.4 climate data.

Table 2
Agricultural land by country from MODIS land cover (code 12 in MOD12Q1 product; Friedl et al., 2010), EUROSTAT data (UAA Utilized Agricultural Area; EUROSTAT, 2015) and CORINE land cover (CLC2000; Büttner and Maucha, 2006) in km^2 representing condition in year 2000. First column provides the total land area for each country. For CORINE we also show the shares of agriculture and pasture land of total land area for each country.

Country	Area	MODIS	EUROSTAT	CORINE land cover			
	(km^2)	Croplands (km^2)	UAA (km^2)	Agriculture (km^2)	Share	Pasture (km^2)	Share
Albania	28,655	20,089	10,903	8139	28%	432	2%
Austria	83,945	20,505	33,807	27,270	32%	7480	9%
Belgium	30,651	18,985	13,957	17,616	57%	3567	12%
Bosnia	51,527	24,599	21,844	18,889	37%	4083	8%
Bulgaria	111,024	80,175	55,821	57,391	52%	4126	4%
Croatia	55,888	23,810	11,687	22,514	40%	2995	5%
Czech Republic	78,755	45,590	42,825	45,232	57%	6414	8%
Denmark	42,710	27,554	26,501	32,164	75%	525	1%
Estonia	45,850	8559	9858	14,679	32%	2570	6%
Finland	332,834	2386	22,086	28,681	9%	18	0%
France	548,056	296,221	297,191	328,526	60%	87,043	16%
Germany	357,221	195,057	170,642	213,573	60%	45,160	13%
Greece	130,012	53,410	47,211	51,548	40%	692	1%
Hungary	92,989	75,547	58,544	62,868	68%	6763	7%
Ireland	69,639	38,091	44,432	46,504	67%	35,457	51%
Italy	299,991	129,328	156,277	156,895	52%	4253	1%
Kosovo	10,896	0	4088	4469	41%	202	2%
Latvia	64,557	17,664	15,872	28,279	44%	8505	13%
Liechtenstein	176	23	0	46	26%	14	8%
Lithuania	64,988	40,892	24,664	39,917	61%	4249	7%
Luxembourg	2581	1688	1346	1411	55%	301	12%
Macedonia	25,463	17,984	12,365	9509	37%	2087	8%
Monaco	9	0	0	0	0%	0	0%
Montenegro	13,215	7896	2222	2143	16%	198	1%
Netherlands	35,568	21,335	19,687	24,909	70%	10,638	30%
Norway	317,644	1337	10,422	15,614	5%	218	0%
Poland	311,658	213,960	182,204	196,166	63%	27,064	9%
Portugal	91,535	21,260	39,569	40,444	44%	382	0%
Romania	237,312	162,720	148,107	134,835	57%	25,211	11%
Serbia	74,500	62,671	35,944	43,092	58%	1536	2%
Slovakia	48,915	23,667	24,022	23,728	49%	2752	6%
Slovenia	20,421	5200	5090	7108	35%	1181	6%
Spain	506,141	165,913	253,938	253,929	50%	6490	1%
Sweden	446,014	9248	29,741	38,705	9%	2467	1%
Switzerland	41,489	7292	15,251	11,790	28%	3774	9%
United Kingdom	244,349	146,792	388,830	141,645	58%	66,304	27%
Europe	4,917,180	1,987,448	2,236,949	2,150,227	44%	375,153	8%

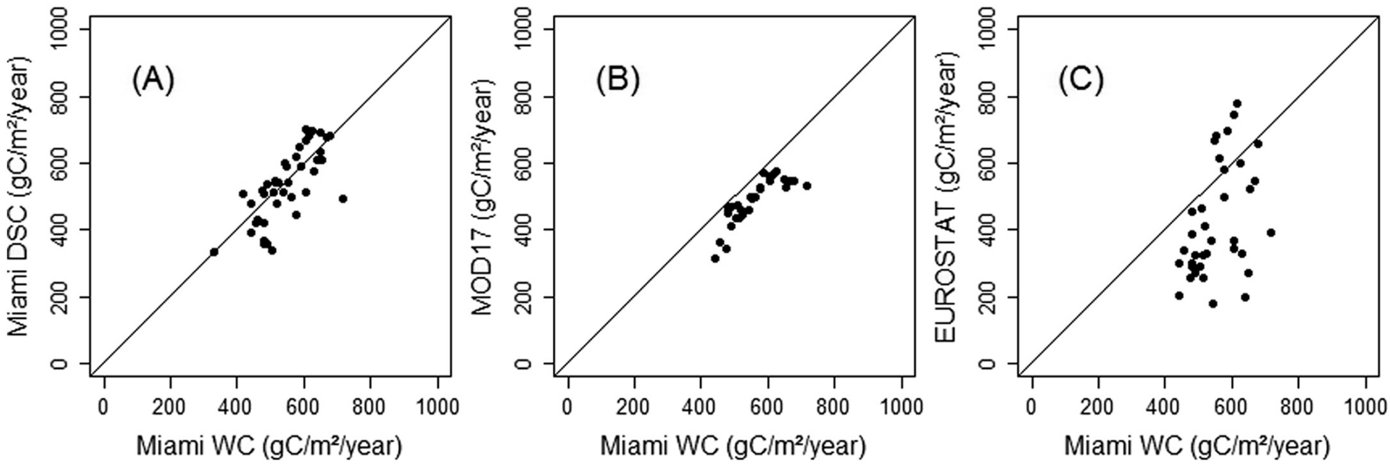

Fig. 3. Crop NPP comparison on country level. Panel A shows results using the Miami model with WorldClim (WC) input (1960–1990) vs. using current downscaled climate data (DSC). In panel B we compare Miami WC with NPP calculated using the MOD17 algorithm. Panel C shows the comparison of EUROSTAT NPP (ensemble mean of 12 estimates) versus Miami WC. The solid line represents the 1:1 relationship.

3.2. Productivity gap analysis at country scale

The Miami model (Lieth, 1975) provides potential NPP limited by climate conditions only and represents realistic, conservative crop productivity estimates compared to four more sophisticated global crop models (Figs. S3–S5). Comparing three Miami NPP estimates using long-term historic climatic averages (WorldClim v1.4) from 1960 to 1990 (Hijmans et al., 2005), using WorldClim v2.0 from 1970 to 2000 (Fick and Hijmans, 2017) and current climate from 2000 to 2012 (Moreno and Hasenauer, 2016) and plotting the latter two in Fig. 3A showed no obvious deviation, which suggests that climate in the last 50 years did not have a clear unidirectional effect on potential NPP. A clear difference became visible when plotting potential NPP using WorldClim v1.4 data against MOD17 NPP (Fig. 3B), where potential NPP exceeds MOD17 NPP for all European countries. Using other Miami estimates does not change this pattern (not shown). However, when comparing Miami NPP and EUROSTAT NPP (mean of ensemble) we got a more differentiated picture (Fig. 3C). While for most countries potential NPP is higher than EUROSTAT (suggesting that some potential production is lost due to sub-optimal management or losses due to e.g. pests and diseases), there are some countries where there is a negative productivity gap (potential NPP smaller than observed NPP; suggesting that management is so effective that it is able to exceed those for which the Miami model was parameterized) (Zheng et al., 2003).

We next explored the productivity gap spatially by calculating the difference between Miami and MOD17 and EUROSTAT respectively, aggregated to country scale (Fig. 4). We only used cropland pixels based on MODIS land cover (Fig. 1). There is substantial variation within countries, and countries in the south and eastern European countries have, in general, a productivity gap (i.e. actual production is lower than potential production), both using MOD17 and EUROSTAT NPP. The largest productivity gaps are found in Portugal, the Baltic and Balkan countries (Fig. 4E).

3.3. Comparison of carbon allocation of croplands and forests

Finally we explored fractions of NPP between forests and croplands using literature information compiled by this study for crops (Table 2) and for forests based on Malhi et al. (2011). We used these fractions to estimate three components of NPP (roots, residues and harvest) and plotted the result temporally using MOD17 of all croplands vs. all forests in Europe (Fig. 5).

By converting MOD17 output into NPP fractions we can also provide a remote-sensing-based estimate of aboveground increment for forests and yield for crops. In Table 3 we compared estimated yield with observed yield using EUROSTAT crop yield and forest inventory data from Neumann et al. (2016a). The complete coverage allows high-quality large-scale comparisons and upscaling to the European scale.

4. Discussion

Croplands cover almost half of the European land area, particularly in Central Europe (Fig. 1, Table 2) and are very important for carbon (C) cycling, with an NPP of 476 ± 51 g C m^{-2} year^{-1} based on yield statistics and 500 ± 82 g C m^{-2} year^{-1} based on the MOD17 algorithm (Fig. 2, Table 3). Our results are in line with an analysis using multiple biogeochemical models and yield statistics and average crop NPP ranging from 482 to 846 g C m^{-2} year^{-1} (Ciais et al., 2010). NPP of European forests, on average, ranges from 536 to 577 g C m^{-2} year^{-1}, based on forest inventory and MOD17 data (Neumann et al., 2016b), and is thus only about 10% higher than crop NPP based on this study. Total crop NPP in Europe based on yield statistics is 927 Mt C each year and total European forest NPP based on MODIS EURO is 850 Mt C each year (Table 3). This highlights the necessity for including agricultural land in global C assessments, not only in terms of the interactions of agricultural land with the atmosphere via albedo (Kirschbaum et al., 2011), but also regarding their seasonal C uptake. C uptake information provided by this study refers to total C uptake, that is then allocated into plant biomass. Estimating different pools of C within the ecosystem requires information or assumptions on turnover rates, decomposition and removal by harvesting and/or disturbances (Seidl et al., 2014). Woody forest biomass is rich in xylem and lignin (Thomas and Martin, 2012) and exhibits lower turnover rates and higher residence time than grasses, annual crops or forbs (Zhang et al., 2008).

European agricultural lands are highly diverse and include many different species with varying traits and life spans ranging from annual crops with aboveground yield such as cereals, belowground crops such as roots and tubers, but also permanent crops such as grasslands, meadows, fruit orchards and vineyards (Tables 2, 3). All crop types need consideration to quantify the entire agriculture productivity. Yield statistics, such as EUROSTAT crop statistics, are an excellent source for information on harvested mass as well as C allocation (Monfreda et al., 2008; Niedertscheider et al., 2016). EUROSTAT crop statistics, however, do not provide information on harvested production for permanent grasslands and pastures, potentially due to difficulties in recording harvest for such areas. Since about 10% of Europe is covered by pastures, and pastures represent more than half of agricultural land

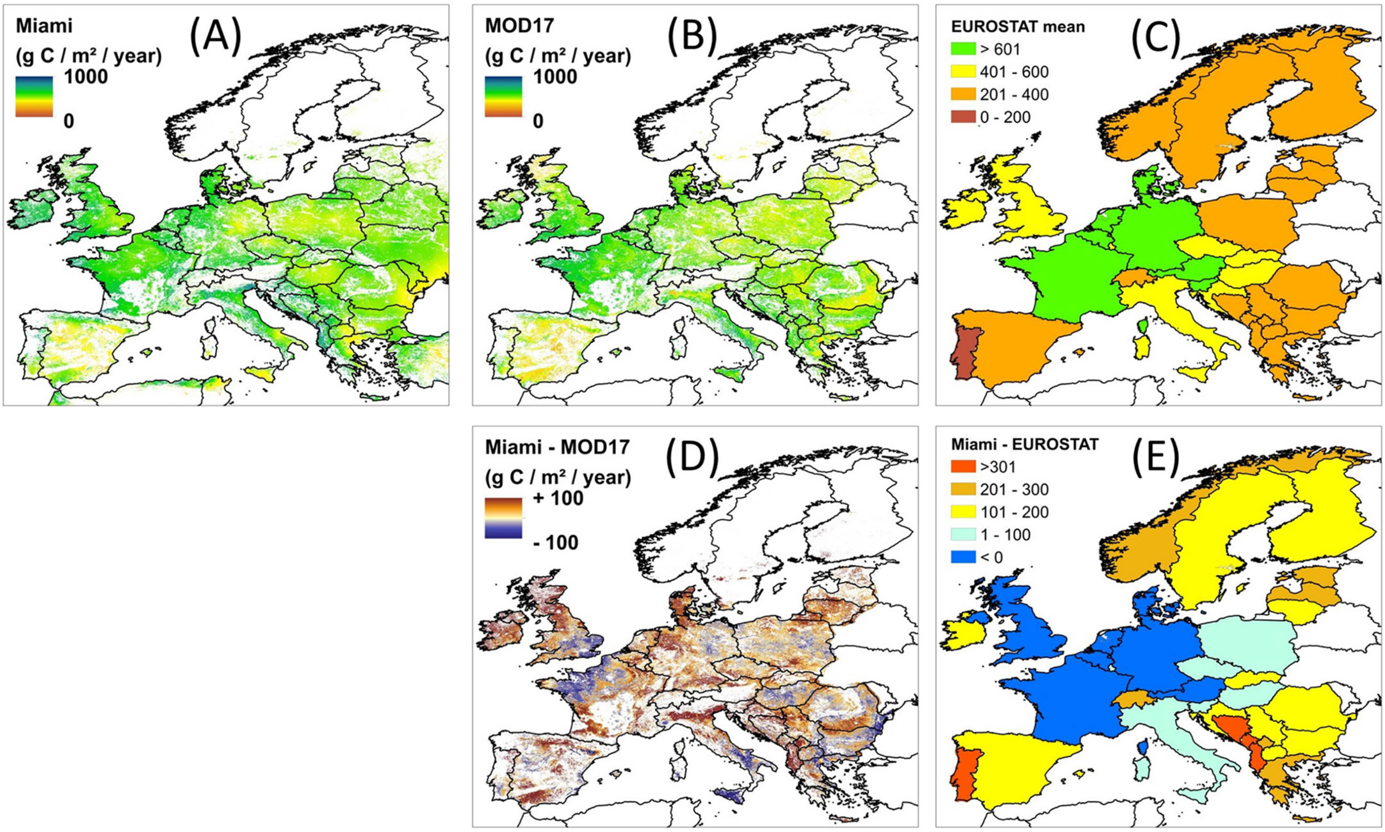

Fig. 4. Spatially-explicit comparison of crop NPP across Europe. In the top row we show NPP using the Miami model (panel A), MOD17 NPP (panel B) and EUROSTAT (panel C, ensemble mean of 12 estimates). On the bottom row we show the productivity gap (difference between potential and observed NPP) for MOD17 in panel D and EUROSTAT in panel E (i.e., positive numbers in red indicate that potential NPP exceeds observed NPP and there is potential to enhance crop productivity).

in some countries (Table 2), EUROSTAT data do not always cover all agricultural production sufficiently.

Suitable models, in combination with remote sensing information, could be useful for complete assessments of agricultural production providing crop NPP, but also an estimate for harvested yield, which can be validated with reference data (Table 3). MOD17 NPP provides a reliable, spatial (1-km resolution) and temporally explicit (annually since 2000) source of productivity information from an ongoing satellite-mounted multispectral sensor. This model can be applied using other satellite products (Sentinel program, Landsat) providing data at even higher resolutions (Immitzer et al., 2016). This study, for the first time, shows how crop productivity and its temporal variation can be examined in a spatially-explicit manner, independently of available terrestrial data (Figs. 2, 4).

Estimates of C uptake based on yield statistics exhibit large variations depending on the conversion parameters used (Table 1, Fig. S2). Even for the same region, the parameters vary by up to 100% (water content of plants harvested green) or even more (root-shoot ratio of permanent crops, Table 1). Just changing the carbon content from 45% to 50%, with both values often used in the literature, increases the estimated C uptake by 10%. Before reliable consistent European data on water content, harvest index, root-shoot ratio and carbon content are available, MOD17 NPP (including a quantified error margin), may provide a robust indicator of the productivity potential of croplands.

Robust productivity information allows quantification of the apparent productivity gaps, or even yield gaps, of agricultural regions (Van Ittersum et al., 2013). Previous research indicated that MOD17 may not properly capture all crop types (Bandaru et al., 2013) and is highly dependent on reliable climate input (Neumann et al., 2016b). Thus, NPP from MOD17 has to be interpreted with caution and may represent average crop productivity, contaminated by trees, shrubs and/or weeds within crop pixels. The Miami model (Lieth, 1975) provides robust estimates of potential NPP of climax ecosystems close to their potential. NPP of forests and crops can be as high as Miami NPP (Zheng et al., 2003), which indicates that these land cover types could be quite effective in utilizing their environmental conditions. Comparing Miami NPP with potential NPP estimates from four independent crop models indicate that the Miami model provides realistic and conservative estimates of potential NPP (Figs. S3–S5). This suggests that the simple Miami model captures the basic conditions of plant growth and the results do not differ irrespective of the used model type (three are spatial-temporal explicit process-based crop models - GEPIC, LPJmL, PEPIC; one is an empirical statistical model using 95th percentile of observed yield binned into climate classes - EarthStat) and made assumptions (assuming full irrigation by the process-based models and assuming climate analogy by the empirical model). On the other hand, crop models require detailed input information for instance on soil, management or crop types and for some important crop types no model parametrization are available (Elliott et al., 2015; Van Ittersum et al., 2013). In addition, currently only information on yield is available, thus the outputs of crop models represent only a fraction of entire carbon uptake by agricultural plants (Fig. 5). Models combined with remotely sensed vegetation information like Miami and MOD17 provide NPP at high spatial resolution capturing small-scale terrain features, fragmented land cover and degradation and management effects. Furthermore, Miami and MOD17 NPP describe also vegetables, fallow land, grassland and perennial crops, which represent a substantial share of the European agricultural land (Fig. 1, Tables 2 and 3).

This study also shows that observed crop productivity in Europe is equal to, or locally even exceeds, potential NPP (Figs. 2, 3). This suggests

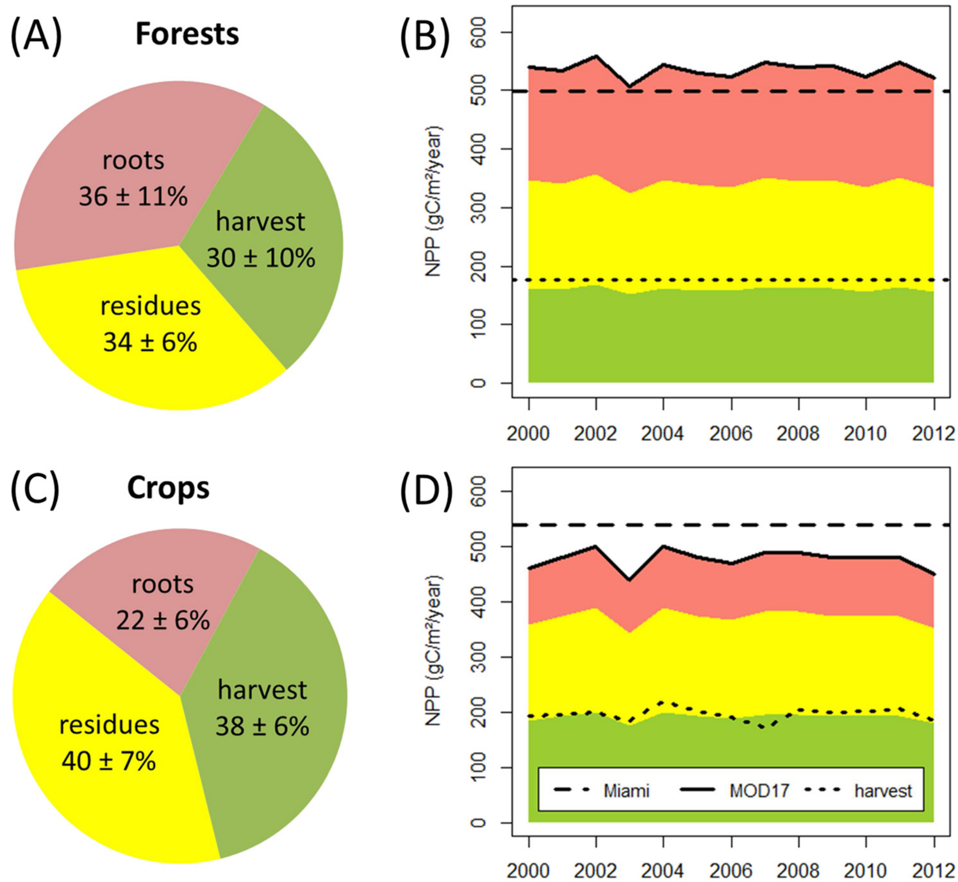

Fig. 5. Harvested compartments (green), aboveground residues (yellow) and belowground roots (red) for forests (panels A, B) and crops (panels C, B). Harvest represents aboveground increment and yield that could be harvested sustainably (in forests the increment is often only partly harvested). Residues are harvestable (e.g. silage maize, historic litter raking or removing branches as fuel wood) and roots are unharvested parts (one exception is extraction of stumps). We show mean and standard deviation of the percent of NPP (A, C) and European average NPP fractions between 2000 and 2012 using MOD17 NPP (B, D). For comparison we show potential NPP using Miami model (dashed) and observed harvest (dotted line) based on forest inventory data and EUROSTAT crop statistics.

that European agricultural lands overall are well managed for high productivity, since their productivity is close to, or even exceeds, their estimated potential. An alternative interpretation would be that the Miami model provides biased results for some regions and/or needs recalibration (Zaks et al., 2007), since conceptually current productivity cannot surpass potential productivity. An evaluation of the Miami model, however, indicated that current NPP can exceed potential NPP, particularly for croplands (Zheng et al., 2003).

While NPP from MOD17 is locally higher than potential NPP (blue regions in Fig. 4D), when aggregated on country level, MOD17 does not exceed potential NPP (Fig. 3B). At a landscape scale, the Miami model seems to represent the upper-limit of plant productivity (European average 571 g C m^{-2} $year^{-1}$), which is about 12% higher than MOD17 (500 g C m^{-2} $year^{-1}$) as well as EUROSTAT NPP (ensemble average 476 g C m^{-2} $year^{-1}$). Based on our results, European agriculture has an overall productivity gap of about 12%, and the climatic conditions would allow for about 10% higher productivity if managed optimally.

On smaller country-level scales, we observed a negative yield gap (i.e. observed NPP is higher than potential NPP) not only for MOD17 NPP (Fig. 4D) but also for EUROSTAT NPP (Figs. 3C, 4E). Agriculture in Central-western European countries (Fig. 4E) appears able to exceed estimated potential NPP at the landscape scale. Certain crop types, cultivars and hybrids, in particular when combined with fertilizers, may have exceedingly high growth rates (Sinclair et al., 2004; Tester and Langridge, 2010). Reasons may involve high light-use efficiency (Bandaru et al., 2013) or drought resistance (Sinclair et al., 2004). Conceptually the productivity gap could be negative, since potential NPP

Table 3
Forests and cropland area (terrestrial based on EUROSTAT and FOREST EUROPE data, remote sensing based on MODIS land cover), MOD17 NPP, estimated harvest using MOD17 NPP and observed harvest by forest inventory (Neumann et al., 2016b) and EUROSTAT (mean and standard deviation, for observed forest harvest we show median and 25th and 75th percentiles to accommodate the skewness). We also show the numbers for the most important crop types, if available.

Land cover	Area (Mio. ha)		MOD17 NPP	MOD17 harvest	Observed harvest
	Terrestrial	Remote sensing	(g C m^{-2} $year^{-1}$)	(t C ha^{-1} $year^{-1}$)	(t C ha^{-1} $year^{-1}$)
Forests	181.8	158.7	536 ± 182	1.61 ± 0.55	1.76 (0.89–3.13)
All crops	194.8	198.9	500 ± 82	1.90 ± 0.36	1.70
Annual crops	101.5	–	–	–	2.10
Permanent grasslands	64.5	–	–	–	–
Permanent crops	11.9	–	–	–	0.84
Fallowland	11.7	–	–	–	–

was calibrated with observed productivity from potential natural vegetation, when the model was developed in the 1970s (Lieth, 1975). Thus the Miami model may not properly represent current conditions and provide potential productivity for conditions that were optimal during the calibration and parameterization of the model about 50 years ago (Zheng et al., 2003).

On the other hand, in eastern, southern and northern Europe, productivity based on reported yield is well below estimated potential NPP and there is a productivity gap (Fig. 4E), which is usually observed worldwide (Neumann et al., 2010). This may relate to lost harvest due to catastrophes (extreme events, pest and disease) or poor management such as low or poor use of fertilizers and/or unsuitable cultivars (Mueller et al., 2012; Oerke, 2006). Enhanced crop management, breeding, irrigation and fertilizer use may increase the yield, for instance, in the Balkans, the Baltic States and Portugal (Fig. 4C). The Miami model provides a conservative and robust estimate of potential NPP; yet comparing with data from other crop models indicate that the potential productivity could be much higher, in particular for irrigated C4 plants like maize (Fig. S3). Comparing NPP based on yield statistics with potential NPP may highlight regions where the agricultural system is deficient in utilizing the local growth conditions. Remotely sensed NPP may be useful when yield statistics are not available or are not reliable, since MOD17 agrees well with EUROSTAT NPP at continental scale (Fig. 2).

In addition to NPP, the remote-sensing based approach of MOD17 can also provide consistent and reliable measures of crop yield and forest increment, independent of available terrestrial data (Fig. 5). Splitting MOD17 NPP with allocation fraction values from the literature (this study, Malhi et al., 2011), provides harvested yield (crops) and sustainable harvestable increment (forests) that agree with crop yield statistics (this study, Fig. 2) and forest inventory data (Neumann et al., 2016b). Such information may be useful for temporal or cross-border analysis of C uptake or resource assessments for regions without any terrestrial data. Robust, large-scale estimates of increment rates may help to ensure sustainable management of forest ecosystems (Forest Europe, 2015) or quantify C uptake rates for emission reduction projects such as REDD+ (Angelsen et al., 2009). European forests exhibit a high in situ C storage with total biomass stocks of about 10.000 Mt C and a density of about 70 t C ha^{-1}, both numbers based on forest inventory data (Forest Europe, 2015; Moreno et al., 2017). Upscaling observed crop yield and forest increment, however, revealed that C allocation by European agriculture into harvested products (331 Mt C using EUROSTAT area, 338 Mt C based on MODIS land cover) is larger than C allocation into harvestable forest biomass (292 Mt C using FOREST EUROPE data, 255 Mt C using MODIS land cover), irrespective of which area information is used (Table 3). While forests exhibit higher NPP than crops (536 vs. 500 g C m^{-2} $year^{-1}$), the C allocation of forests into harvestable compartments is lower than for crops (Fig. 4). Since agricultural land covers a larger area than forests, the total C flux into agricultural biomass is larger. Forests, however, allocate a larger amount of C into forest floor and soil pools via rhizodeposition and litterfall (Fig. 4). Such information could be used for modelling C pools using decomposition models for forests as well as for agricultural land (Liski et al., 2005; Smith et al., 2006). Smart use of crop residues, roots and waste material, for instance by producing bioenergy for substituting fossil fuels, may create long-term C sequestration effects, since the C that is otherwise left on the field or in landfills would be eventually emitted to the atmosphere under current management practices (Cherubini and Ulgiati, 2010).

In conclusion, C uptake by European agricultural land is greater than in forests, showing the importance of including agricultural land in global assessments, but our results also show that agricultural NPP is lower than potential NPP in a number of European areas, indicating that it is possible in these regions to improve the efficiency of agriculture and increase C uptake further. We have shown that models, combined with remotely sensed data can be used to estimate or verify statistical production estimates for croplands, and to identify areas where productivity could be improved. When also considering previous applications in forestry, we have also shown that these methods are robust across different landscape types, providing a consistent approach for use across entire landscapes to consistently estimate C uptake at continental scale.

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Author contributions

M.N. and P.S. conceived and designed the research; M.N. did the data analysis and visualization; M.N. and P.S. wrote and revised the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.06.268.

References

Angelsen, A., Brockhaus, M., Kanninen, M., Sills, E., Sunderlin, W., Wertz-Kanounnikoff, S., 2009. Realising REDD+: National Strategy and Policy Options. CIFOR, Bogor, Indonesia.
Bandaru, V., West, T.O., Ricciuto, D.M., César Izaurralde, R., 2013. Estimating crop net primary production using national inventory data and MODIS-derived parameters. ISPRS J. Photogramm. Remote Sens. 80:61–71. https://doi.org/10.1016/j.isprsjprs.2013.03.005.
Bondeau, A., Smith, P.C., Zaehle, S., Schaphoff, S., Lucht, W., Cramer, W., Gerten, D., Lotze-campen, H., Müller, C., Reichstein, M., Smith, B., 2007. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. Glob. Chang. Biol. 13: 679–706. https://doi.org/10.1111/j.1365-2486.2006.01305.x.
Brisson, N., Gate, P., Gouache, D., Charmet, G., Oury, F.X., Huard, F., 2010. Why are wheat yields stagnating in Europe? A comprehensive data analysis for France. F. Crop. Res. 119:201–212. https://doi.org/10.1016/j.fcr.2010.07.012.
Büttner, G., Maucha, G., 2006. The thematic accuracy of Corine land cover 2000. EEA Tech. Rep. 90.
Chen, W., Chen, J.M., Price, D.T., Cihlar, J., 2002. Effects of stand age on net primary productivity of boreal black spruce forests in Ontario, Canada. Can. J. For. Res. 32:833–842. https://doi.org/10.1139/x01-165.
Cherubini, F., Ulgiati, S., 2010. Crop residues as raw materials for biorefinery systems - a LCA case study. Appl. Energy 87:47–57. https://doi.org/10.1016/j.apenergy.2009.08.024.
Ciais, P., Wattenbach, M., Vuichard, N., Smith, P., Piao, S.L., Don, A., Luyssaert, S., Janssens, I.A., Bondeau, A., Dechow, R., Leip, A., Smith, P., Beer, C., Van Der Werf, G.R., Gervois, S., Van Oost, K., Tomelleri, E., Freibauer, A., Schulze, E.D., 2010. The European carbon balance. Part 2: croplands. Glob. Chang. Biol. 16:1409–1428. https://doi.org/10.1111/j.1365-2486.2009.02055.x.
de Wit, A.J.W., van Diepen, C.A., 2008. Crop growth modelling and crop yield forecasting using satellite-derived meteorological inputs. Int. J. Appl. Earth Obs. Geoinf. 10: 414–425. https://doi.org/10.1016/j.jag.2007.10.004.
Elliott, J., Mueller, C., Deryng, D., Chryssanthacopoulos, J., Boote, K.J., Buechner, M., Foster, I., Glotter, M., Heinke, J., Iizumi, T., Izaurralde, R.C., Mueller, N.D., Ray, D.K., Rosenzweig, C., Ruane, A.C., Sheffield, J., 2015. The global gridded crop model intercomparison: data and modeling protocols for phase 1 (v1.0). Geosci. Model Dev. 8: 261–277. https://doi.org/10.5194/gmd-8-261-2015.
EUROSTAT, 2015. Europe in Figures - Eurostat Yearbook.
FAO, 2011. The State of the World's Land and Water Resources for Food and Agriculture. Managing Systems at Risk. Food and Agriculture Organization (doi:978-1-84971-326-9).
Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37:4302–4315. https://doi.org/10.1002/joc.5086.
Forest Europe, 2015. State of Europe's Forests 2015. Ministerial Conference on the Protection of Forests in Europe FOREST EUROPE Liaison Unit Madrid, Spain.
Friedl, M., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., Huang, X., 2010. MODIS Collection 5 global land cover: algorithm refinements and characterization of new datasets. Remote Sens. Environ. 114:168–182. https://doi.org/10.1016/j.rse.2009.08.016.

Gobin, A., Campling, P., Janssen, L., Desmet, N., van Delden, H., Hurkens, J., Lavelle, P., Berman, S., 2011. Soil organic matter management across the EU- best practices, constraints and trade-offs. Final Rep. Eur. Comm. DG Environ. 180. https://doi.org/10.2779/17252.

Haberl, H., Erb, K.H., Krausmann, F., Gaube, V., Bondeau, A., Plutzar, C., Gingrich, S., Lucht, W., Fischer-Kowalski, M., 2007. Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. Proc. Natl. Acad. Sci. 104:12942–12947. https://doi.org/10.1073/pnas.0704243104.

Hansen, M.C., Defries, R.S., Townshend, J.R.G., Sohlberg, R., 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. Int. J. Remote Sens. 21:1331–1364. https://doi.org/10.1080/014311600210209.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25:1965–1978. https://doi.org/10.1002/joc.1276.

Immitzer, M., Vuolo, F., Atzberger, C., 2016. First experience with Sentinel-2 data for crop and tree species classifications in central Europe. Remote Sens. 8. https://doi.org/10.3390/rs8030166.

Kirschbaum, M., Whitehead, D., Dean, S.M., Beets, P.N., Shepherd, J.D., Ausseil, A.-G.E., 2011. Implications of albedo changes following afforestation on the benefits of forests as carbon sinks. Biogeosciences 8:3687–3696. https://doi.org/10.5194/bg-8-3687-2011.

Kirschbaum, M., Saggar, S., Tate, K.R., Thakur, K.P., Giltrap, D.L., 2013. Quantifying the climate-change consequences of shifting land use between forest and agriculture. Sci. Total Environ. 465:314–324. https://doi.org/10.1016/j.scitotenv.2013.01.026.

Lieth, H., 1975. Modelling the primary productivity of the world. In: Lieth, H., Whittaker, R. (Eds.), Primary Productivity of the Biosphere. Springer-Verlag, New York, pp. 237–263.

Liski, J., Palosuo, T., Peltoniemi, M., Sievänen, R., 2005. Carbon and decomposition model Yasso for forest soils. Ecol. Model. 189:168–182. https://doi.org/10.1016/j.ecolmodel.2005.03.005.

Lobell, D.B., Schlenker, W., Costa-Roberts, J., 2011. Climate trends and global crop production since 1980. Science 333:616–620. https://doi.org/10.1126/science.1204531 (80-.).

Malhi, Y., Doughty, C., Galbraith, D., 2011. The allocation of ecosystem net primary productivity in tropical forests. Philos. Trans. R. Soc. Lond. Ser. B Biol. Sci. 366: 3225–3245. https://doi.org/10.1098/rstb.2011.0062.

Monfreda, C., Ramankutty, N., Foley, J.A., 2008. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Glob. Biogeochem. Cycles 22:1–9. https://doi.org/10.1029/2007GB002947.

Monteith, J., 1972. Solar radiation and productivity in tropical ecosystems. J. Appl. Ecol. 9, 747–766.

Montero, G., Ruiz-Peinado, R., Munoz, M., 2005. Produccion de biomasa y fijacion de CO_2 por los bosques espanoles. Monogr. INIA 13, 270.

Moreno, A., Hasenauer, H., 2016. Spatial downscaling of European climate data. Int. J. Climatol. 36:1444–1458. https://doi.org/10.1002/joc.4436.

Moreno, A., Neumann, M., Hasenauer, H., 2017. Forest structures across Europe. Geosci. Data J. 4:17–28. https://doi.org/10.1002/gdj3.45.

Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Foley, J.A., 2012. Closing yield gaps through nutrient and water management. Nature 490:254–257. https://doi.org/10.1038/nature11420.

Neumann, K., Verburg, P.H., Stehfest, E., Müller, C., 2010. The yield gap of global grain production: a spatial analysis. Agric. Syst. 103:316–326. https://doi.org/10.1016/j.agsy.2010.02.004.

Neumann, M., Moreno, A., Mues, V., Härkönen, S., Mura, M., Bouriaud, O., Lang, M., Achten, W.M.J., Thivolle-Cazat, A., Bronisz, K., Merganič, J., Decuyper, M., Alberdi, I., Astrup, R., Mohren, F., Hasenauer, H., 2016a. Comparison of carbon estimation methods for European forests. For. Ecol. Manag. 361:397–420. https://doi.org/10.1016/j.foreco.2015.11.016.

Neumann, M., Moreno, A., Thurnher, C., Mues, V., Härkönen, S., Mura, M., Bouriaud, O., Lang, M., Cardellini, G., Thivolle-Cazat, A., Bronisz, K., Merganič, J., Alberdi, I., Astrup, R., Mohren, F., Zhao, M., Hasenauer, H., 2016b. Creating a regional MODIS satellite-driven net primary production dataset for European forests. Remote Sens. 8:1–18. https://doi.org/10.3390/rs8070554.

Neumann, M., Mues, V., Moreno, A., Hasenauer, H., Seidl, R., 2017. Climate variability drives recent tree mortality in Europe. Glob. Chang. Biol. 23:4788–4797. https://doi.org/10.1111/gcb.13724.

Neumann, M., Ukonmaanaho, L., Johnson, J., Benham, S., Vesterdal, L., Novotný, R., Verstraeten, A., Lundin, L., Thimonier, A., Michopoulos, P., Hasenauer, H., 2018. Quantifying carbon and nutrient input from litterfall in European forests using field observations and modeling. Glob. Biogeochem. Cycles 32:784–798. https://doi.org/10.1029/2017GB005825.

Niedertscheider, M., Kastner, T., Fetzel, T., Haberl, H., Kroisleitner, C., Plutzar, C., Erb, K.-H., 2016. Mapping and analysing cropland use intensity from a NPP perspective. Environ. Res. Lett. 11, 14008. https://doi.org/10.1088/1748-9326/11/1/014008.

Oerke, E.-C., 2006. Crop losses to pests. J. Agric. Sci. 144:31. https://doi.org/10.1017/S0021859605005708.

Palosuo, T., Kersebaum, K.C., Angulo, C., Hlavinka, P., Moriondo, M., Olesen, J.E., Patil, R.H., Ruget, F., Rumbaur, C., Takáč, J., Trnka, M., Bindi, M., Çaldaĝ, B., Ewert, F., Ferrise, R., Mirschel, W., Şaylan, L., Šiška, B., Rötter, R., 2011. Simulation of winter wheat yield and its variability in different climates of Europe: a comparison of eight crop growth models. Eur. J. Agron. 35:103–114. https://doi.org/10.1016/j.eja.2011.05.001.

R Development Core Team, 2016. R: A Language and Environment for Statistical Computing. R Found. Stat. Comput, Vienna, Austria.

Scurlock, J.M., Olson, R.J., 2002. Terrestrial net primary productivity a brief history and a new worldwide database. Environ. Rev. 10:91–109. https://doi.org/10.1139/a02-002.

Seidl, R., Schelhaas, M.-J., Rammer, W., Verkerk, P.J., 2014. Increasing forest disturbances in Europe and their impact on carbon storage. Nat. Clim. Chang. 4:806–810. https://doi.org/10.1038/nclimate2318.

Sinclair, T.R., Purcell, L.C., Sneller, C.H., 2004. Crop transformation and the challenge to increase yield potential. Trends Plant Sci. 9:70–75. https://doi.org/10.1016/j.tplants.2003.12.008.

Smith, P., 2004. Carbon sequestration in croplands: the potential in Europe and the global context. Eur. J. Agron. 20:229–236. https://doi.org/10.1016/j.eja.2003.08.002.

Smith, P., Smith, J., Wattenbach, M., Meyer, J., Lindner, M., Zaehle, S., Hiederer, R., Jones, R.J.A., Rounsevell, M., Montanarella, L., Reginster, I., Kankaanpää, S., 2006. Projected changes in mineral soil carbon of European forests, 1990–2100. Can. J. Soil Sci. 86: 159–169. https://doi.org/10.4141/S05-078.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C., Scholes, B., Sirotenko, O., Howden, M., McAllister, T., Pan, G., Romanenkov, V., Schneider, U., Towprayoon, S., Wattenbach, M., Smith, J.U., 2008. Greenhouse gas mitigation in agriculture. Philos. Trans. R. Soc. Lond. Ser. B Biol. Sci. 363:789–813. https://doi.org/10.1098/rstb.2007.2184.

Smith, P., Lanigan, G., Kutsch, W.L., Buchmann, N., Eugster, W., Aubinet, M., Ceschia, E., Béziat, P., Yeluripati, J.B., Osborne, B., Moors, E.J., Brut, A., Wattenbach, M., Saunders, M., Jones, M., 2010. Measurements necessary for assessing the net ecosystem carbon budget of croplands. Agric. Ecosyst. Environ. 139:302–315. https://doi.org/10.1016/j.agee.2010.04.004.

Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E.A., Haberl, H., Harper, R., House, J., Jafari, M., Masera, O., Mbow, C., Ravindranath, N.H., Rice, C.W., Robledo Abad, C., Romanovskaya, A., Sperling, F., Tubiello, F., M., J., 2014. Agriculture, forestry and other land use (AFOLU). In: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kriemann, B., Savolainen, J., Schlömer, S., von Stechow, C., Zwickel, T. (Eds.), Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, USA: pp. 811–922 https://doi.org/10.1016/j.phrs.2011.03.002.

Tester, M., Langridge, P., 2010. Breeding technologies to increase crop production in a changing world. Science 327:818–822. https://doi.org/10.1126/science.1183700 (80-.).

Thomas, S.C., Martin, A.R., 2012. Carbon content of tree tissues: a synthesis. Forests 3: 332–352. https://doi.org/10.3390/f3020332.

Tubiello, F.N., Salvatore, M., Rossi, S., Ferrara, A., Fitton, N., Smith, P., 2013. The FAOSTAT database of greenhouse gas emissions from agriculture. Environ. Res. Lett. 8, 15009. https://doi.org/10.1088/1748-9326/8/1/015009.

Turner, D.P., Ritts, W.D., Cohen, W.B., Maeirsperger, T.K., Gower, S.T., Kirschbaum, A.A., Running, S.W., Zhao, M., Wofsy, S.C., Dunn, A.L., Law, B.E., Campbell, J.L., Oechel, W.C., Kwon, H.J., Meyers, T.P., Small, E.E., Kurc, S.A., Gamon, J.A., 2005. Site-level evaluation of satellite-based global terrestrial gross primary production and net primary production monitoring. Glob. Chang. Biol. 11:666–684. https://doi.org/10.1111/j.1365-2486.2005.00936.x.

Turner, D.P., Ritts, W.D., Cohen, W.B., Gower, S.T., Running, S.W., Zhao, M., Costa, M.H., Kirschbaum, A., Ham, J.M., Saleska, S.R., Ahl, D.E., 2006. Evaluation of MODIS NPP and GPP products across multiple biomes. Remote Sens. Environ. 102:282–292. https://doi.org/10.1016/j.rse.2006.02.017.

Van Ittersum, M.K., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., Hochman, Z., 2013. Yield gap analysis with local to global relevance-a review. F. Crop. Res. 143:4–17. https://doi.org/10.1016/j.fcr.2012.09.009.

West, P.C., Gibbs, H.K., Monfreda, C., Wagner, J., Barford, C.C., Carpenter, S.R., Foley, J.A., 2010. Trading carbon for food: global comparison of carbon stocks vs. crop yields on agricultural land. Proc. Natl. Acad. Sci. U. S. A. 107:19645–19648. https://doi.org/10.1073/pnas.1011078107.

Zaks, D.P.M., Ramankutty, N., Barford, C.C., Foley, J.A., 2007. From Miami to Madison: investigating the relationship between climate and terrestrial net primary production. Glob. Biogeochem. Cycles 21. https://doi.org/10.1029/2006GB002705.

Zhang, D.Q., Hui, D.F., Luo, Y.Q., Zhou, G.Y., 2008. Rates of litter decomposition in terrestrial ecosystems: global patterns and controlling factors. J. Plant Ecol. 1:85–93. https://doi.org/10.1093/Jpe/Rtn002.

Zhao, M., Running, S.W., 2010. Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. Science 329:940–943. https://doi.org/10.1126/science.1192666.

Zhao, M., Heinsch, F.A., Nemani, R.R., Running, S.W., 2005. Improvements of the MODIS terrestrial gross and net primary production global data set. Remote Sens. Environ. 95:164–176. https://doi.org/10.1016/j.rse.2004.12.011.

Zheng, D., Prince, S., Wright, R., 2003. Terrestrial net primary production estimates for 0.5° grid cells from field observations-a contribution to global biogeochemical modeling. Glob. Chang. Biol. 9:46–64. https://doi.org/10.1046/j.1365-2486.2003.00534.x.